Predicting personality traits of facebook users using text mining

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PREDICTING PERSONALITY TRAITS OF FACEBOOK USERS USING TEXT MINING

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ABSTRACT

Currently, social media is used to express the users' opinion, perception and so on. Status created by social media users describes the characteristics of their personality. This research was conducted to find out the traits of social media users on Facebook by mining the users' Facebook posts. The texts were categorized and classified using SVM, Naïve Bayes and Logistic Regression in order to get the traits of each user. The data for this case study was taken from Indonesian users of Facebook. The result of this mining was compared to the results of the previous research. To handle the problem of imbalanced user data, synthetic minority over-sampling technique (SMOTE) was used. The results of this study indicated that the results generated using the proposed method successfully outperformed the results of the previous research with an average accuracy of 89.08%.

Keywords: *Text Mining, Personality Prediction, SMOTE, SVM, Naïve Bayes, Logistic Regression*

1. INTRODUCTION

Personality detection based on human appearance has been an interesting topic in the domain of psychology [1] as it has profound implications in studying personal interactions. Most of the studies in psychology about personality recognition are from texts in which they focus on the analysis of textual samples. Various researchers also found a strong correlation between linguistic features and characteristics of personality [2][3]. There are several models used in predicting personality such as Big Five Personality, MBTI (Myers Briggs Type Indicator) and DISC (Dominance Influence Steadiness Conscientiousness). Big Five Personality was chosen and used in this study because the personality model is most widely used and appropriate in predicting one's personality. In addition, it is consistently used in interviews, self-description and observation [4], [5]. Big Five Personality or commonly known as 5 (five) personality traits consists of Openness to Experience, Conscientiousness, Extraversion, Agreeableness and Neuroticism.

However, in the process of collecting the personality data from social media, data imbalance in each class often occurs. The result of research conducted by Andangsari et al clearly exhibits this tendency. On one hand, their analysis on data set of the training class revealed that 92 users have high trait whereas 237 users have low trait in Conscientiousness and 202 users have high trait and 127 users have low trait in Extraversion. On the other hand, their data set of testing class showed 21 users have high trait whereas 9 users have low trait in Neuroticism and 24 users have high trait while 6 users have low trait in Extraversion [6]. The same data imbalance is also evident in the research conducted by Tandera et al. The dataset that they obtained from myPersonality revealed that 96 users have high trait and 154 users have low trait in Extraversion whereas 99 users have high trait and 151 users have low trait in Neuroticism [5]. In other words, as mentioned previously, data imbalance often occurs during the process of collecting the data. The data imbalance in each class of personality traits would generate problems in the classification process; the results of classification on the machine learning would always generate predictions on classes with the highest number of data, which would lead to errors in predicting personality [7]. There are three approaches that can be adopted in dealing with the data imbalance. First is the approach at the data level, the second is the approach based on the algorithm level, and the last is by using a combination of learning methods by combining several classification methods [7]. To adopt the approach at the data level in order to deal with the data imbalance, sampling technique can be used. By applying sampling technique, the problem of data

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imbalance can be reduced, and the accuracy can be improved. There are two kinds of sampling techniques: undersampling and oversampling. Oversampling technique is a technique of balancing the amount of data distribution by increasing the number of data in classes with low number of data. Undersampling technique is a technique of reducing the amount of data in classes with high number of data [7].

In this study, the authors adopted approach at the data level. In addition, in order to deal with the problem of data imbalance, oversampling technique was applied. One of the famous oversampling techniques is the Synthetic Minority Oversampling Technique (SMOTE). The SMOTE method works by creating new synthetic data on classes with low number of data, so the data will be balanced in each class [8].

In this paper, the authors proposed the use of SMOTE in predicting personality. The use of SMOTE can help in overcoming the data imbalance to improve the accuracy of classifiers in predicting the personality based on the users' posts on their Facebook wall.

2. LITERATURE REVIEW

Many studies have been conducted in predicting personality on Facebook. For example, Pednekar and Duney conducted a study in identifying the nature of personality using social media with data mining approach [9], Agarwal, in his research, detected personality using text on myPersonality corpus [10], and Kosinski et al, in their research, identified the personality patterns of Facebook users [11]. Most of the research in this area was conducted on Facebook posts in English. However, it is also possible to analyze posts in other languages such as Chinese [12] and Indonesian [5]. This study would focus on analyzing Facebook posts in Indonesian, just like the research on the prediction of personality on Facebook posts in Indonesian conducted by Tandera et al with the topic of personality prediction system from Facebook Users [5].

2.1 The Big 5 Personality

According to Golbeck Personality Dimension "Big 5" is one of the best personality measures to serve as a research model and is considered good in measuring one's personality. The Big 5 traits are characterized by the following [13]:

a. Openness to Experience: curious, intelligent, imaginative. High scorers tend to be artistic and sophisticated in taste and appreciate diverse views, ideas, and experiences.
b. Conscientiousness: responsible, organized, persever- ing. Conscientious individuals are extremely reliable and tend to be high achievers, hard workers, and planners.
c. Extroversion: outgoing, amicable, assertive. Friendly and energetic, extroverts draw inspiration from social situations.
d. Agreeableness: cooperative, helpful, nurturing. Peo- ple who score high in agreeableness are peace-keepers who are generally optimistic and trusting of others.
e. Neuroticism: anxious, insecure, sensitive. Neurotics are moody, tense, and easily tipped into experiencing negative emotions.

2.2 Text Mining

According to Talib et al Text mining is a process to extract interesting and significant patterns to explore the knowledge of text data sources. Text mining is a multi-disciplinary field based on information retrieval, data mining, machine learning, statistics, and computational linguistics [14]. While Salloum et al in his research says that Text mining is an easy way to get data that has meaning and structured from irregular data patterns. It really is not an easy task for the computer to understand unstructured data and make it structured [15].

2.3 Bag Of Words

Bag of Words is a model that represents objects globally such as text or documents as a word (multiset) word regardless of grammar and even word order to preserve its diversity [16]. Bag of Words is a common method used to represent documents in the fields of Information Retrieval (IR) and Natural Language Processing (NLP) [12]. In words, BoW is a collection of unique words in the document. A simple example of forming a bag-of-words for text documents as follows. If there is a document in indonesian "*Sari senang membaca novel, Ina juga penggemar novel remaj*a (Sari loves reading novels, Ina is also a fan of teen novels)". Then the text can be compiled into BoW, using a unique word represented just once so as to form a different order then calculated the frequency of occurrence shown in Table 2.3 [16].

Table 1. Example Bag Of Word

Word	Frequency Distribution

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Sari	1
Senang	1
Membaca	1
Novel	2
Ina	1
Juga	1
Penggemar	1
Remaja	1

2.4 SMOTE (*Synthetic Minority Oversampling Technique*)

Synthetic Minority Oversampling Technique (SMOTE) is one oversampling method that works by increasing the number of positive classes through random data replication, so the amount of positive data equals negative data. How to use synthetic data is to replicate data in a small class. The SMOTE algorithm works by finding the nearest neighbor k for the positive class, then building synthetic data duplication as much as the desired percentage between the randomly selected and positive k classes. Overall it is formulated into equation 1 [7].

$$x_{syn} = x_i + (x_{knn} - x_i) \times \delta \qquad (1)$$

Where δ is a random number between 0 and 1. The SMOTE algorithm is shown in Figure 1.

Algorithm *SMOTE*(T, N, k)
Input: Number of minority class samples T; Amount of SMOTE N%; Number of nearest neighbors k
Output: (N/100)* T synthetic minority class samples
(∗ If N is less than 100%, randomize the minority class samples as only a random percent of them will be SMOTEd. ∗)
if N <100
then Randomize the T minority class samples
$T = (N/100) * T$
$N = 100$
endif
N =(int)(N/100)(∗ The amount of SMOTE is assumed to be in integral multiples of 100. ∗)
k = Number of nearest neighbors
numattrs = Number of attributes
Sample[ ][ ]: array for original minority class samples
newindex: keeps a count of number of synthetic samples generated, initialized to 0
Synthetic[ ][ ]: array for synthetic samples
(∗ *Compute k nearest neighbors for each minority class sample only.* ∗)
for $i \leftarrow 1$ **to** T
Compute k nearest neighbors for i, and save the indices in the nnarray
Populate(N, i, nnarray)
endfor
Populate(N, i, nnarray)(∗ Function to generate the synthetic samples. ∗)
while $N \neq 0$
Choose a random number between 1 and k,callit nn. This step chooses one of the k nearest neighbors of i.
for $attr \leftarrow 1$ **to** *numattrs*
Compute: $dif = Sampel[nnarray[nn]][attr] - Sample[i][attr]$
Compute: *gap* = random number between 0 and 1
$Sintetis[newindex][attr] = Sampel[i][attr] + gap * dif$
endfor
newindex++
$N = N - 1$
endwhile
return (∗ *End of Populate.* ∗)
End of Pseudo-Code.

Figure 1 : SMOTE Algorithm [17]

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2.5 Support Vector Machines

SVM is a Machine Learning method that works on the principle of Structural Risk Minimization (SRM) in order to find a hyperplane. Hyperplane is the best separator between the two classes on the input space that can be found by measuring the hyperplane's margins and searching for the maximum point. Margin is the distance between the hyperplane and the nearest pattern of each class. The closest pattern is called a support vector [18]. The theory underlying SVM itself has evolved since the 1960s, but it was only introduced by Vapnik, Boser and Guyon in 1992 and since then SVM has been growing rapidly [19].

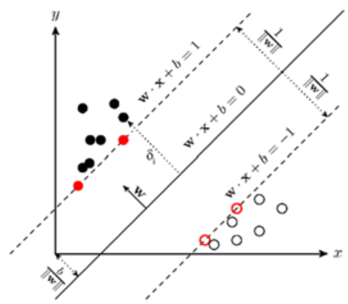

Figure 2 : SVM Overview

Based on Figure 2.1 can be seen there are 2 classes are separated linearly that is class with black circle and class with white sphere. The two classes contained in Figure 2.1 are separated by a transverse line called hyperplane and the equation of the hyperplane line is $w.x + b = 0$, where w is the normal plane and b is the bias (the position of the field relative to the coordinate center). Vectors that have the closest distance to a hyperplane are called support vectors. SVM will split the class using hyperplane with the largest interclass boundary, the hyperplane will form a dividing line parallel to the support vector of all classes [20].

It looks for the best equivalent hyperplane in order to maximize the margin between 2 classes that can be obtained from formula of $\frac{2}{|\vec{w}|}$. It is equal to minimize the function of $\frac{1}{2}\vec{w}\tau\vec{w}$ with the notice barrier of $y_i(\vec{w}\tau\vec{x_i} + b) \geq 1$, with $\vec{x_i}$ is vector data, y_i is class label, and $\vec{w}$, b is the parameters to find the value. Next is the classification problems formulated in quadratic programming (QP). The problem can be solved by using the lag range multiplier, therefore the classification function will be as the following equation 2.

$$f(\vec{x}) = sign\left(\sum\nolimits_i a_i\, y_i \vec{x_i^l}\vec{x} + b\right) \qquad (2)$$

With a_i is a lag range multiplier that correspondents to $\vec{x_i}$ [21].

Using the kernel function, data will transform into infinite-dimensional higher vector spaces. The next step is looking for the field of separation between the two classes in new vector spaces new. The following figure 2 illustrated the vector to infinite-dimensional higher vector space.

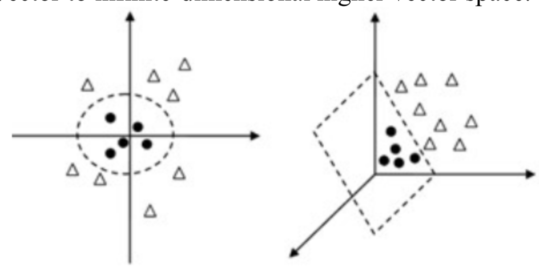

Figure 3 : The Application of Kernels on SVM in Transformation into Dimension Higher [21]

There are several forms of kernel functions most commonly used are linear, polynomial, radial basic function (RBF), and sigmoid. The kernel function used in this research is linear, RBF and polynomial. The RBF kernel is shown in equation 3.

$$K(x_i, x_{i'}) = exp\left(-\gamma \sum_{j=1}^{p} (x_{ij} - x_{i'j}\right) \qquad (3)$$

Where $\gamma > 0$ is an additional tuning parameter specified by gamlma (#). When the test data is very far from the training data, the exponent becomes very negative and $K(x_i, x_{i'})$ approaches zero. The polynomial kernel is shown in equation 4.

$$K(x_i, x_{i'}) = \left(\beta_0 + \gamma \sum_{j=1}^{p} x_{ij} x_{i'j}\right)^d \qquad (4)$$

Where $\gamma > 0$ and β_0 are additional tuning parameters. The parameter γ is determined the same as before and β_0 is determined by coef0 (#). β_0 is "bias" which is the same metric used for all samples.

2.6 Naive Bayes

The Naive Bayes classifier is a simple classifier based on Bayes's theorems of conditional probabilities and independent assumption forces. This classifier emphasizes the probability measurement whether document A belongs to class B or not. It is based on the assumption that the

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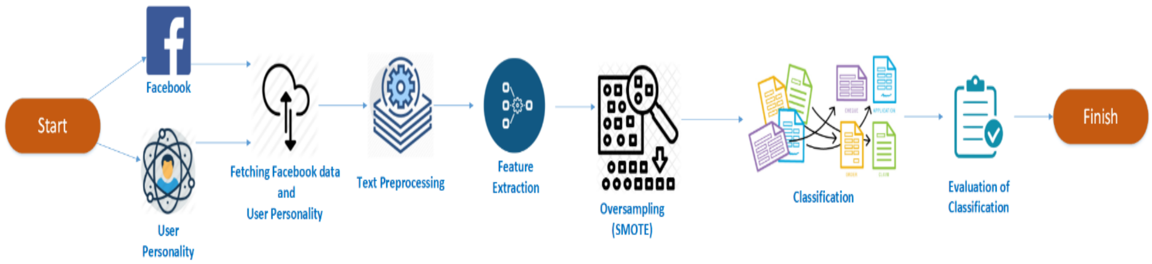

Figure 1: Overview Methodology

incidence or absence of certain attributes. The advantage of the Bayesian classifier is that it requires only a small collection of training data for classification. Easier implementation, faster in classification and more efficient.

This research using Gaussian Naive Bayes. Gaussian is usually used to represent the conditional probabilities of the continue feature in a class $P(X_i|Y)$ and characterized by two parameters: the mean and the variant [22].

3. METHODOLOGY

3.1 The Concepts

The concept of methodology in this study is shown in Figure 1. Based on the illustration in Figure 1, the core steps of this study are as follows:

a. Collecting datasets consisting of personality and post values captured using the Facebook API;
b. Pre-processing text data from Facebook wall posts;
c. Extracting text feature on text data;
d. Oversampling with SMOTE;
e. Classifying with SVM, Naïve Bayes and Logistic Regression;
f. Evaluating results from personality predictions.

3.2 Data Collection

At this stage, information from Facebook users, specifically their posts on their Facebook wall, was collected.

The process of data retrieval was conducted by using the Facebook API via online survey application created by the authors. The online survey app contains a personality measurement tool to determine the personality traits of Facebook users.

Before completing the online personality survey, users were required to log in and connect to their Facebook. After users had filled out the survey, the application would retrieve all information and Facebook posts on the users' Facebook. Afterwards, the application would generate and display the results of personality traits.

The tool which was used to determine the personality is the Big Five Inventory, which consists of 44 items of questions measured using the Likert scale [23]. In order to accommodate the Indonesian Facebook users, the authors utilized the Indonesian translation of the Big Five Inventory from Ramdhani [24].

The online survey was then administered on Indonesian Facebook users across different ages and genders in the academic community.

By the end of data collection stage, 345 participants had filled the survey, and their personality labels were acquired. The responses and information collected from these 345 participants were used as the data for this research. Distribution of manually-gathered dataset from participants can be seen in Table 1.

Table 1. Distribution of Manually-Gathered Dataset

Trait Labels	Amount of Participants		Total
	High Trait	Low Trait	
Openness	281	64	345
Conscientiousness	260	85	345
Extraversion	245	100	345
Agreeableness	319	26	345
Neuroticism	197	148	345

3.3 Text Pre-Processing

At this stage, the texts would undergo the pre-processing step. This step is necessary for data cleansing process in order to ensure that the data are consistent and uniform before the features of the texts were extracted. The stages are shown in Figure 2.

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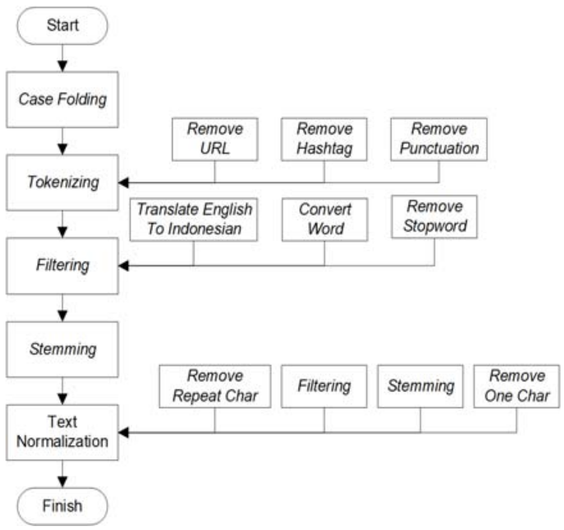

Figure 2 : Stages of Text Pre-Processing

a. Case Folding involves changing all the capital letters found either in the beginning, middle or end of the word into lowercase. For example, the sentence as shown below:

"Aku pernah Kehilangan Semuanya"

would be changed into:

"aku pernah kehilangan semuanya".

b. Tokenizing involves removing all the URLs, hashtags and punctuation found in sentences and separating all sentences into words. For example, the sentence as shown below:

"mungkin bisa di bagi ke teman, saudara dkk alamat survei : https://docs.google.com/forms/d/12gzlkbuzwsdssmxli6xv86kn8uzvqwrnvjsimd7ddcw/viewform"

would be changed into:

" mungkin bisa di bagi ke teman saudara dkk alamat survei".

Then the sentence would be separated into words as follows: "*mungkin*", "*bisa*", "*di*", "*bagi*", "*ke*", "*teman*", "*saudara*", "*dkk*", "*alamat*", and "*survei*".

c. Filtering involves removing words that are considered meaningless using the list of stopwords by Tala [25]. Furthermore, it also involves translating words from English into Indonesian. Non-standard Indonesian words and slang language would be converted into formal Indonesian forms that comply with *Kamus Besar Bahasa Indonesia* (Great Dictionary of the Indonesian Language). For example, the sentence as shown below:

"akhirnya nemuin makanan ini gak berhenti makan deh eating is a talent"

would be changed into:

"menemukan makanan tidak berhenti makan deh makan adalah sebuah talenta".

d. Stemming is the process of eliminating affixes either at the beginning (e.g. *me-, ber-, ter-*, and so on) or at the end of a word (e.g. *–kan, -an, -i,* and so on). For example, the sentence as shown below:

"menemukan makanan berhenti makan deh makan adalah sebuah talenta"

would be converted into:

"temu makan henti makan deh makan adalah sebuah talenta".

e. Text Normalization is the last step in text pre-processing which involves eliminating repetitive letters that cause the wording to be unstructured. Then, the filtering and stemming steps would be repeated before the step of removing one-letter character, which has no meaning, was applied. For example, the sentence as shown below:

"malam michael gilaaaaaaa Baaaaaangeeeeet maju kocak a"

would be converted into:

"malam michael gila banget maju kocak".

3.4 Text Feature Extraction

The feature extraction using TF-IDF resulted in attributes as much as 78.245 words. Despite the fact that the authors filtered the attributes beforehand using corpus generated by the authors themselves, the number of attributes which did not conform to the standard Indonesian language (e.g. abbreviations, slang language, and so on) was abundant.

The results of feature extraction using TF-IDF are shown in Table 2.

Table 2. Results of Feature Extraction

No	Id FB	Results of Feature Extraction In Words							
		ab	aba	ababil	abad	abadi	...	zyrex	zyrus
1	1003191079823600	0	0	0	0	0	...	0	0
2	10154935912923978	0	0	0	0	0,003482	...	0	0
3	10155055753123542	0	0	0	0	0	...	0	0
4	10155072366618863	0	0,008002	0	0,020901	0	...	0	0
5	10155215389501878	0	0	0	0	0,009637	...	0	0
6	10155255826838330	0,002064	0,000899	0	0	0,001426	...	0	0
7	10155529497724819	0	0	0,002064	0	0,001236	...	0	0
8	10155557756948209	0	0	0,00701	0	0	...	0	0
9	10155681265154189	0	0	0	0	0,014645	...	0	0
10	10155691836128060	0	0	0	0	0	...	0	0
11	10155709311850769	0	0,006617	0	0	0,003501	...	0	0
12	10155788105797384	0	0	0	0	0,019692	...	0	0
...	...	...	...	...	...	...	...	...	...
334	10203097618237752	0	0	0,008103	0	0,002427	...	0	0
335	10203252123500426	0,02205	0	0	0	0	...	0	0
336	10203297985446914	0,005196	0	0	0	0	...	0	0
337	10203622786806174	0	0	0	0	0,00619	...	0	0
338	10203728263962789	0,00297	0	0	0	0	...	0	0
339	417352918633342	0	0	0	0	0,034741	...	0	0
340	474603166244015	0	0	0	0	0	...	0	0
341	644925402379296	0	0	0	0	0,004565	...	0	0
342	783210951852242	0	0	0	0	0,003276	...	0	0
343	795672763950111	0	0	0	0	0,009331	...	0	0
344	845588468930259	0	0	0	0	0,029116	...	0	0
345	970033343099640	0	0	0	0	0	...	0	0

3.5 SMOTE (Synthetic Minority Oversampling Technique)

In this research, the SMOTE method was used to handle the problem of data imbalance in the dataset [17]. At this stage, new synthetic data in the class with low number of data were made. The process of creating synthetic data was conducted until the data in each class became balanced with the class that has the highest amount of data. SMOTE was performed after the feature extraction stage was completed, and the output of the SMOTE result was a new synthetic data. The parameters used in the SMOTE method were as follows:

a. The number of nearestNeighbors used is 5;
b. The number of randomSeed (the amount of generator used for oversampling) used is 1;
c. The percentage of SMOTE for each class to be balanced is 77% for Class O, 67% for Class C, 59% for Class E, 91% for Class A and 24% for Class N.

Results of datasets before and after using the SMOTE method are shown in Table 3.

Table 3. Distribution of Manually-Gathered Datasets Before and After Using SMOTE

Traits	Before SMOTE		After SMOTE	
	Yes	No	Yes	No
Openness	281	64	281	281
Conscientiousness	260	85	260	260
Extraversion	245	100	245	245
Agreeableness	319	26	319	319
Neuroticism	197	148	197	197

3.6 Model Classification

The classification algorithm used in this research was SVM with Linear Kernel, RBF Kernel and Polynomial degree 3 with gamma = 1, Gaussian Naïve Bayes, and Logistic Regression. Performance of the classification was measured using the 10 cross-fold validation method for all classification models. The classification process used binary

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classification of 1 and 0 for each class of personality. Next, we randomly split the datasets in 2 groups: training data and testing data. 90% of the dataset was used as training data while the remaining 10% was used as testing data. The whole process of classification used python libraries.

4. RESULTS

The accuracy results of the classification using SVM with Linear Kernel for every 10 attempts are shown in Table 4.

Table 4. The Accuracy Results of Classification Using SVM with Linear Kernel

Fold	Traits(%)				
	Ope	**Con**	**Ext**	**Agr**	**Neu**
1	94,8	88,5	82,0	100,0	67,5
2	91,1	80,8	74,0	100,0	55,0
3	96,4	92,3	82,0	100,0	60,0
4	100,0	96,2	82,0	100,0	60,0
5	98,2	100,0	96,0	100,0	57,5
6	98,2	96,2	87,5	98,4	55,0
7	100,0	98,1	95,8	100,0	57,5
8	100,0	98,1	97,9	100,0	60,5
9	96,4	98,1	95,8	98,4	84,2
10	100,0	96,2	100,0	100,0	89,5
Avg	**97,5**	**94,4**	**89,3**	**99,7**	**64,7**

In Table 4, it can be seen that based on the result of classification using SVM with Linear Kernel, the trait of Agreeableness had the highest degree of average accuracy, which is 99,7%, and it can also be seen that the accuracy reached 100% in Fold 1, 2, 3, 4, 5, 7 , 8 and 10. Meanwhile, the trait of Neuroticism had the lowest degree of average accuracy, which is only 64,7%, and it can be noted as well that the lowest accuracy (55,0%) was in Fold 2 and 6.

The accuracy results of the classification using SVM with RBF Kernel for every 10 attempts are shown in Table 5.

Table 5. The Accuracy Results of Classification Using SVM with RBF Kernel

Fold	Traits(%)				
	Ope	**Con**	**Ext**	**Agr**	**Neu**
1	93,1	78,8	76,0	98,4	60,0
2	89,3	76,9	82,0	100,0	57,5
3	96,4	88,5	70,0	100,0	62,5
4	100,0	94,2	72,0	100,0	72,5
5	100,0	100,0	100,0	100,0	60,0
6	100,0	100,0	100,0	100,0	67,5
7	100,0	100,0	100,0	100,0	60,0
8	100,0	100,0	100,0	100,0	71,1
9	100,0	100,0	100,0	100,0	97,4
10	100,0	100,0	100,0	100,0	97,4
Avg	**97,9**	**93,8**	**90,0**	**99,8**	**70,6**

In Table 5, it can be seen that based on the result of classification using SVM with RBF kernel, the trait of Agreeableness had the highest degree of average accuracy, which is 99,8%, and it can also be seen that the accuracy reached 100% in Fold 2 to 10. Meanwhile, the lowest average accuracy was the trait of Neuroticism with the average accuracy of 70,6%, and it can also be seen that the lowest accuracy (57,5%) was in Fold 2.

The accuracy results of the classification using SVM with Polynomial Kernel for every 10 attempts are shown in Table 6.

Table 6. The Accuracy Results of Classification Using SVM with Polynomial Kernel

Fold	Traits(%)				
	Ope	**Con**	**Ext**	**Agr**	**Neu**
1	94,8	92,3	84,0	100,0	62,5
2	91,1	80,8	86,0	100,0	50,0
3	98,2	90,4	82,0	100,0	62,5
4	100,0	98,1	78,0	100,0	70,0
5	96,4	100,0	100,0	100,0	60,0
6	100,0	100,0	100,0	100,0	65,0
7	100,0	100,0	100,0	100,0	60,0
8	96,4	100,0	100,0	100,0	73,7
9	100,0	100,0	100,0	100,0	97,4
10	96,4	100,0	100,0	100,0	97,4
Avg	**97,3**	**96,2**	**93,0**	**100,0**	**69,8**

The results in Table 6 shows that by using SVM with Polynomial kernel, the highest average accuracy belongs to the trait of Agreeableness (100%), and it is important to note that the accuracy reached 100% in Fold 1 to 10. On the other hand, the lowest average accuracy belongs to the trait of Neuroticism (69,8%), and it can also be seen that the lowest accuracy of 50% was in Fold 2.

The accuracy results of the classification using Gaussian Naïve Bayes for every 10 attempts are shown in Table 7.

Table 7. The Accuracy Results of Classification Using Gaussian Naive Bayes

Fold	Traits(%)				
	Ope	Con	Ext	Agr	Neu
1	98,3	96,2	92,0	100,0	67,5
2	100,0	92,3	90,0	100,0	70,0
3	98,2	94,2	88,0	100,0	57,5
4	100,0	98,1	88,0	100,0	77,5
5	96,4	98,1	96,0	98,4	60,0
6	100,0	98,1	95,8	96,9	57,5
7	100,0	100,0	93,8	100,0	57,5
8	100,0	98,1	97,9	100,0	76,3
9	98,2	90,4	91,7	100,0	78,9
10	91,1	88,5	87,5	91,9	78,9
Avg	**98,2**	**95,4**	**92,1**	**98,7**	**68,2**

Based on the results in Table 7, by using Gaussian Naïve Bayes, the highest average accuracy belongs to the trait of Agreeableness with the average accuracy of 98,7%. In addition, it is important to note that the accuracy reached 100% in Fold 1, 2, 3, 4, 7, 8 and 9. Meanwhile, the lowest average accuracy belongs to the trait of Neuroticism with the average accuracy of 68,2%, and it can also be seen that the lowest accuracy (57,5%) was in Fold 3, 6 and 7.

The accuracy results of the classification using Logistic Regression for every 10 attempts are shown in Table 8.

Table 8. The Accuracy Results of Classification Using Logistic Regression

Fold	Traits(%)				
	Ope	Con	Ext	Agr	Neu
1	91,4	80,8	70,0	96,9	62,5
2	64,3	67,3	66,0	100,0	57,5
3	83,9	84,6	64,0	100,0	55,0
4	98,2	92,3	70,0	100,0	55,0
5	85,7	100,0	92,0	100,0	50,0
6	92,9	94,2	83,3	100,0	57,5
7	96,4	94,2	89,6	100,0	52,5
8	94,6	92,3	93,8	100,0	57,9
9	94,6	96,2	85,4	98,4	81,6
10	92,9	94,2	97,9	100,0	76,3
Avg	**89,5**	**89,6**	**81,2**	**99,5**	**60,6**

Based on the results on Table 8 above, it is evident that by using Logistic Regression, the highest average accuracy belongs to the trait of Agreeableness with the average accuracy of 99,5%, and the accuracy in fact reached 100% in Fold 2, 4, 5, 6, 7, 8, and 10. On the other hand, the lowest average accuracy belongs to the trait of Neuroticism (60,6%) in which the lowest accuracy, which is 50%, was in Fold 5.

The results explained above would be compared to the results of research by Tandera et al. Tandera et al also used SVM, Gaussian Naïve Bayes, and Logistic Regression as their classification algorithm. For the comparison on accuracy, two scenarios were employed. For the first scenario, datasets from myPersonality website were used while for the second scenario, the authors used datasets which are collected manually as conducted by Tandera et al [5].

The comparison on the accuracy results for the first scenario using SVM algorithm is shown in Figure 3. In this case, the authors used SVM with Polynomial Kernel for the proposed method.

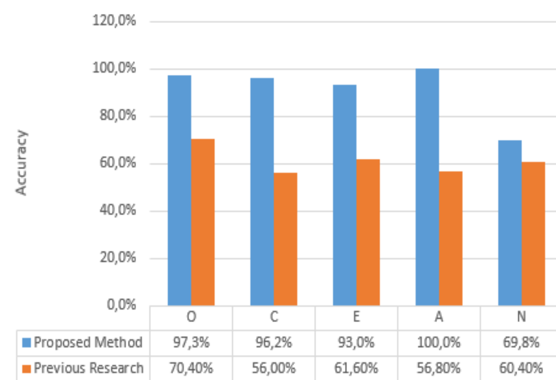

Figure 3 : Comparison on Accuracy Result Using SVM with Polynomial Kernel for First Scenario

The comparison on the accuracy results for the first scenario using Gaussian Naïve Bayes for the proposed method is shown in Figure 4.

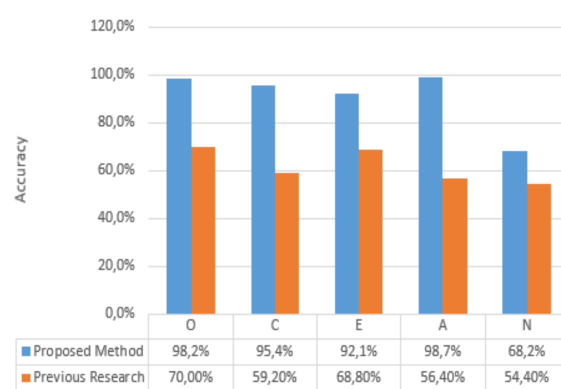

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Figure 4 : Comparison on Accuracy Result Using Gaussian Naïve Bayes for First Scenario

The comparison on the accuracy results for the first scenario using Logistic Regression for the proposed method is shown in Figure 5.

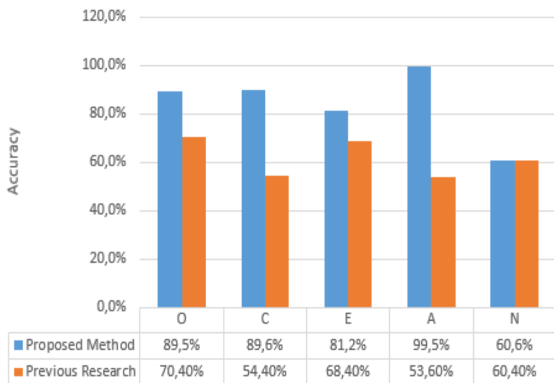

Figure 5 : Comparison on Accuracy Result Using Logistic Regression for First Scenario

Based on Figure 3, 4 and 5, for the first scenario, the traits of Openness, Conscientiousness, Extraversion and Agreeableness show significant increase in accuracy when compared to the previous study. However, the trait of Neuroticism only shows slight increase in accuracy.

The comparison on the accuracy results for the second scenario using SVM algorithm is shown in Figure 6. In this case, the authors used SVM with Polynomial Kernel for the proposed method.

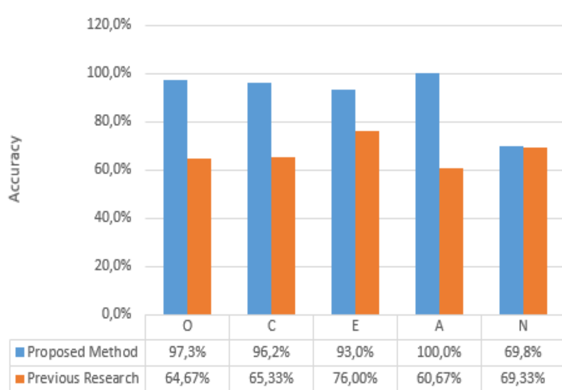

Figure 6 : Comparison on Accuracy Result Using SVM with Polynomial Kernel for Second Scenario

The comparison on accuracy results for the second scenario using Gaussian Naïve Bayes for the proposed method is shown in Figure 7.

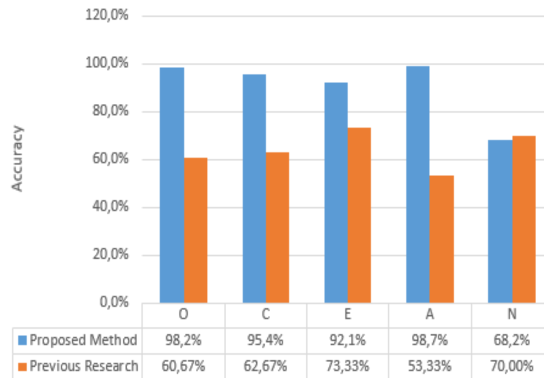

Figure 7 : Comparison on Accuracy Result Using Gaussian Naïve Bayes for Second Scenario

The comparison on accuracy results for the second scenario using Logistic Regression for the proposed method is shown in Figure 8.

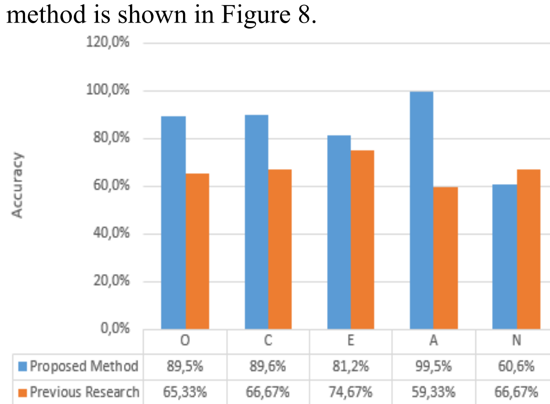

Figure 8 : Comparison on Accuracy Result Using Logistic Regression for Second Scenario

Similar to the first scenario, there is significant increase in accuracy for the traits of Openness, Conscientiousness, Extraversion and Agreeableness. However, the trait of Neuroticism using SVM with Polynomial Kernel shows only slight increase by 0,47% in accuracy. Meanwhile, the method used in previous study exhibits better accuracy than the proposed method when Gaussian Naïve Bayes and Logistic Regression algorithm were used.

5. CONCLUSION

This experiment has successfully predicted the personality of Facebook users with SVM, Naïve Bayes and Logistic Regression as the text mining techniques and SMOTE as the algorithm for solving the problem of data imbalance. In each experiment, the authors measured and tested the SVM, Gaussian Naïve Bayes and Logistic Regression models using the 10-fold cross validation method to obtain accuracy rate in each fold. The experimental results show that the performance of SVM classification model with Linear, Polynomial and RBF kernels, and Gaussian Naïve Bayes and Logistic Regression has an excellent accuracy in predicting the personality. In predicting personality traits of Openness, Conscientiousness, Extraversion and Agreeableness have an average accuracy rate above 80%. It also proves that the SMOTE algorithm works well in dealing with the issue of data imbalance.

In addition, the accuracy of this study was also compared to the results of research conducted by Tandera et al using 2 scenarios: by using datasets from myPersonality website and by using manually-collected datasets.

From the comparison for the first scenario, it can be concluded that the proposed method was successful in increasing the accuracy of personality prediction for all classification models. Moreover, it can be seen that there is significant increase in accuracy, especially in the trait of Openness. By using the Gaussian Naïve Bayes classification model, the trait of Openness reached the highest accuracy of 98,2%.

In the second scenario, the comparison of accuracy results also shows similar phenomenon in which there is significant increase in accuracy level in the traits of Openness, Conscientiousness, Extraversion and Agreeableness. The highest accuracy in the second scenario is the trait of Openness using Gaussian Naïve Bayes in which the accuracy rate reached 98,2%. However, compared to the trait of Openness, there is no increase in accuracy for the trait of Neuroticism from using Gaussian Naïve Bayes and Logistic Regression. It could be seen from the fact that by using the proposed method, the accuracy for the trait of Neuroticism only reached 68,2% whereas the result of the previous research reached 70%.

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